# Integrating AI/ML Techniques in Parametric Modeling for Creative Design

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### Abstract

Parametric modeling is a fast way to create design variations but has limitations such as subjective parameter selections and constrained design variables. This study enhances parametric modeling by integrating AI/ML techniques, fostering creativity and innovation. The authors use deep learning algorithms to analyze 2D chair images, extract latent features, and employ t-SNE for visualization and parametrization of the features in 3D models. We also use 3D Generative Adversarial Networks (3DGANs) and conversational AI (ChatGPT) as design tools for novel chair designs, expanding design possibilities. This study demonstrates the potential for innovative design solutions, transforming the design process and suggesting new research directions.

## Introduction

Professionals in creative domains, such as art, design, and architecture, have used parametric modeling to synthesize a multitude of design solutions by adjusting parameters during the modeling process, especially in trade-off relationships (Cross 2021). This method can rapidly generate a vast set of design variations, allowing designers to explore different possibilities, to define design problems more accurately, and to explore the opportunities and limitations of potential solutions (Schumacher 2015).

Despite its advantages, parametric modeling in the design area has several limitations. One limitation is the 'subjectivity' involved in parameter selection, as it depends on the designer's experience, knowledge, aesthetics, and personal preferences (Krish 2011). This subjectivity can often act as a double-edged sword: it provides a human's creativity and design uniqueness, but on the other hand, it could inadvertently limit the range of design possibilities explored (Menges and Ahlquist 2011). This is because individual biases, conscious or unconscious, could restrict the designer's perspective and the parameters chosen, potentially overlooking novel or unconventional design solutions that lie outside the designer's habitual thinking patterns. Another limitation is that the design variations generated by parametric models are inherently constrained by parameter interpolation. Iterative design exploration in the parametric modeling process focuses on individual parameters, rather than examining their inter-relationships (Yamamoto and Nakakoji 2005). As a result, entirely new designs cannot be created once the parameters are set, leading to a limited range of design possibilities and restricting the exploration of novel design solutions.

To address these limitations and enhance the design process, this study explores the integration of AI/ML techniques with parametric design methods to foster creativity and innovation in parametric modeling. The study aims to generate unique, dynamic, and innovative designs by using deep learning (DL) algorithms to analyze 2D chair images and extract latent feature space. Following this, we employ a dimensionality reduction algorithm (t-SNE) to visualize data distribution across the feature space, which serves as visual feedback for constructing parameters in the 3D model. This alternative approach allows for a more comprehensive exploration of the design space and facilitates the generation of novel design solutions, complementing human creativity and circumventing potential cognitive limitations in the design process. .

Furthermore, to expand the range of design possibilities beyond the constraints of parametric models, this study employs Generative AI models, 3D Generative Adversarial Networks (3DGANs), to create new 3D chair designs from the dataset generated by the parametric model. This approach allows for the generation of completely new design forms that are not limited by the initial parameter interpolation, thereby enabling greater design innovation.

This paper also explores conversational AI (ChatGPT) and its potential in design processes. This study demonstrates the unexpected generation of shapes and design solutions that are not reliant on predefined parameters. This approach offers a new method for designers to interact with design tools and discover unconventional design possibilities.

This study contributes to the existing body of research by bridging the gap between AI/ML techniques and parametric design methodologies. We demonstrate the potential for creating novel design processes and innovative design solutions that combine the strengths of both AI/ML and design methodologies through the application of deep learning algorithms, generative AI models, and conversational AI ChatGPT.

The paper is organized into the following sections: Section 2 describes the AI/ML augmented parametic modeling

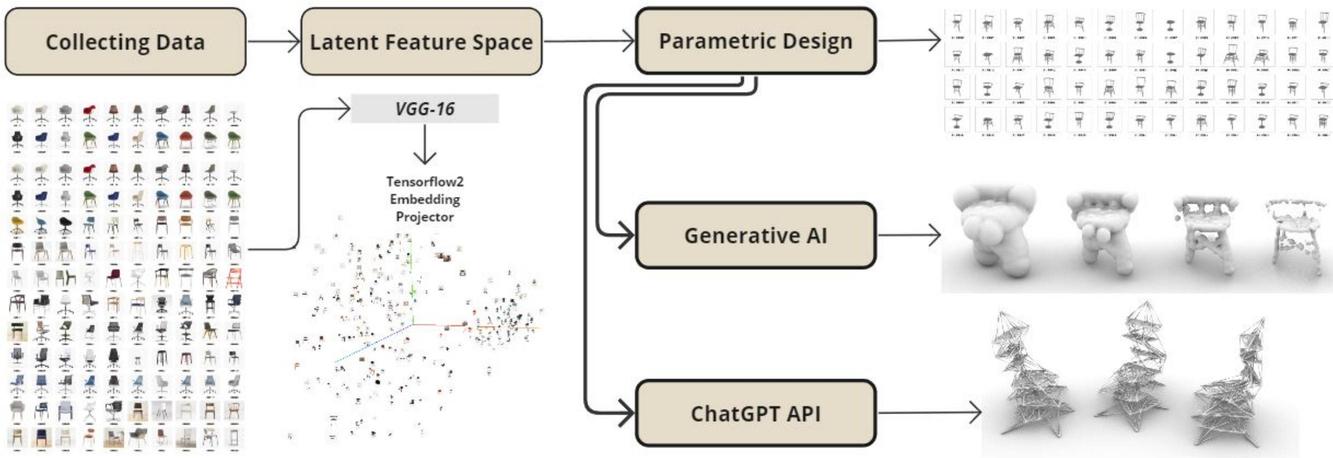


Figure 1: The overall process of parametric modeling and interaction with AI/ML technologies

process and illustrates how a feature space can contribute to design exploration and generation. Section 3 and 4 discuss the 3DGANs design and ChatGPT API implementation processes. Then, the advantages and limitations will be discussed with regard to integrating AI/ML techniques with parametric design methods, addressing the potential future research. (Figure 1)

## Augmented AI/ML in Parametric Modeling

To conduct a manageable modeling process and meaningful geometric exploration, we chose chairs as the subject due to their significance in design history and their wide-ranging variety in form, function, and style (Cranz 1998). We randomly selected 300 chairs from the book '1000 chairs' by Charlotte & Peter Fiell (Fiell and Fiell 1997), ensuring a balanced representation of the diverse range of styles, including mid-century, Scandinavian, Brazilian, and others, in order to minimize bias in our dataset. The images were preprocessed to a resolution of 512x512 pixels, resulting in a feature vector of size 262,144.

Design Feature Space Generation

For the extraction of feature vectors, we utilized the VGG-16 model (Simonyan and Zisserman 2014) since the VGG-16 model has been widely adopted and proven effective in various applications, making it a reliable choice for our study (He et al. 2016). Additionally, this paper focuses on exploring the integration of AI/ML techniques with parametric design methods rather than achieving higher accuracy in feature extraction.

After obtaining the feature vectors, we used t-SNE, a dimensionality reduction algorithm (Van der Maaten and Hinton 2008), in TensorFlow's Embedding Projector to visualize the distribution of these features in a lower-dimensional space (Smilkov et al. 2016). This visualization allowed us to identify and analyze distinct clusters of chair designs. (Figure 2)

Parametric modeling process

There are no previous approaches to extracting the latent design space features and incorporating them into the para-

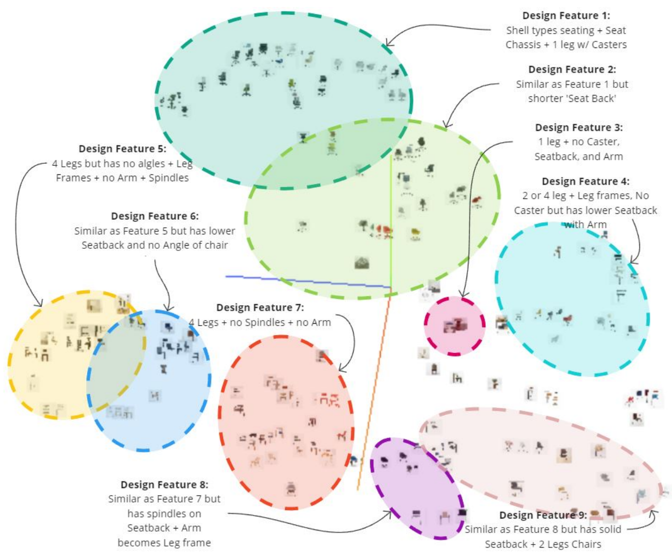


Figure 2: Latent space analysis to extract design features

metric design process. We extracted 9 distinct design features through the Embedding Projector and captured key aspects of chair design: Seat_shell, Seat_seat, Seat_back, Arm, Seat_base, Seat_chassis, Leg_frame, Leg, and Caster. These features were identified through careful analysis by practice experienced designers and faculties (Maxwell 2012).

Manual feature extraction, in particular, allows for incorporating domain knowledge into the design process. Therefore, designers can leverage their expertise to identify and select the most relevant features.

This methodology reflects the perspective of a designer and allows for the incorporation of human intuition and creativity in the AI/ML-augmented design process

To construct a parametric model, we organized design features using the following categories. The most prominent classification question started with "Does the chair have a shell seat or not?". For each category, different parametric rules were established based on factors such as the 'seat shape', 'number of legs', 'leg angles', and 'presence or absence of arm rest'. All generated 1000 chairs are shown in Figure 3.

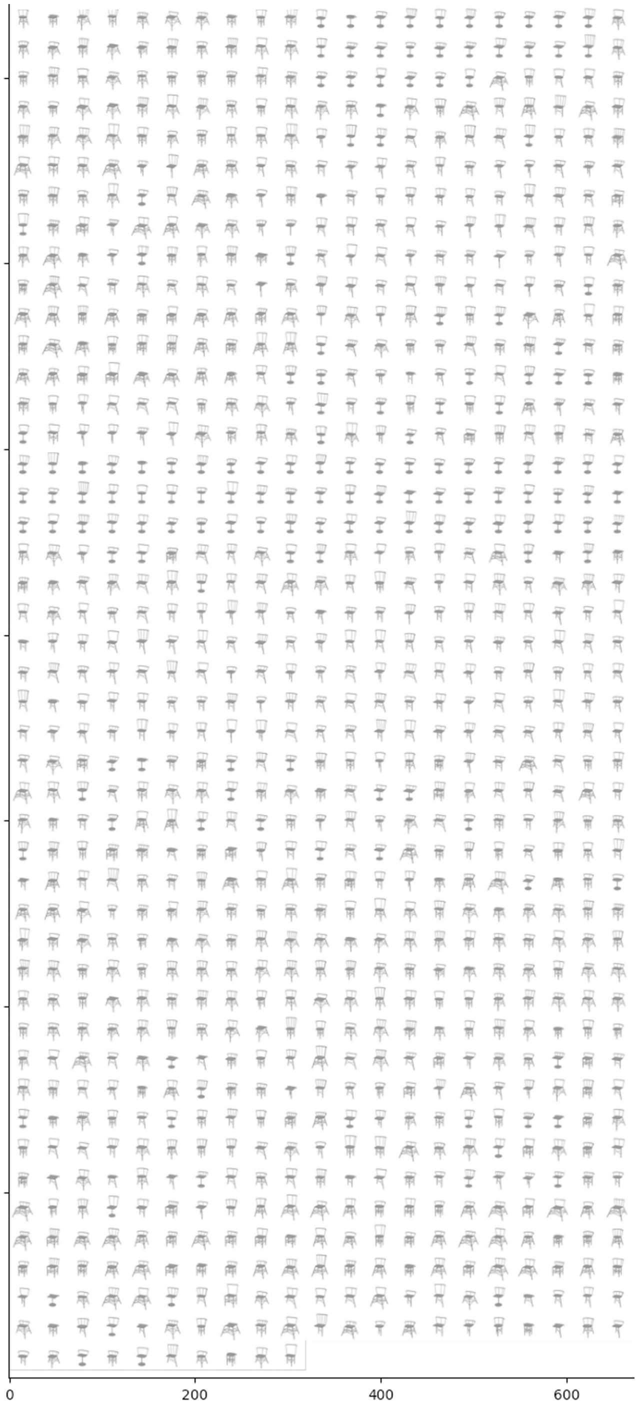


Figure 3: 1000 new chair designs resulting from parametric modeling

**- Seat shape:** We adjusted the 'fillet' parameters at all four corners, enabling the circular seat form generation. Moreover, when the arm's portions exceed the seat's radian value at a certain threshold, the parametric model decides that the chair has an integrated 'Arm' and 'Seat_back' together.

**- Number of Legs:** We accounted for a range of 1 to 4 legs. Implementing a Lloyd Algorithm, which repeatedly updates the centroid positions and assigns data points to their nearest centroids until convergence (Du, Emelianenko, and Ju 2006), we enabled the application of a bridge to the center point of each split plane. In cases where the seat shape is circular, we observed that the leg's center point falls outside the chair seat. To overcome the challenge of creating parametric models that cover all these scenarios, we derived a relational expression using a regression model, applying the position coordinate value to predict all different case scenarios.

**- Leg Angle**: Through feature space analysis, we verified that additional frames are braced when the leg angle surpasses a specific angle.

By assigning random values to each parameter, a thousand distinct chairs were generated, addressing the potential for innovative and unexpected outcomes when combining human creativity with computational power.

The AI/ML augmented parametric modeling process expanded the possibilities of the existing parametric design process by leveraging computational capabilities to identify, synthesize, analyze, and classify patterns and characteristics of the data, tasks which are extremely challenging for humans.

## Generative AI/ML in Parametric Modeling

While parametric modeling is an iterative process that focuses on the variation of individual parameters and struggles with comparison and selection, 3DGANs can learn complex relationships among the parameters and generate new designs based on the distribution of data in the latent space (Zhang et al. 2019). In contrast to utilizing 3D geometry libraries such as ShapeNet (Chang et al. 2015), we trained the 3DGAN on a dataset of 3D models generated through the parametric modeling process. This approach allows the 3DGAN to learn the underlying structure and dependencies between the parameters, resulting in the generation of diverse and innovative design solutions that go beyond the predefined parametric space.

### Data Preprocessing and Training for 3DGAN

In this experiment, the main goal was to extract features from 3D chair models rather than high-resolution data. The models were voxelized into 64-sized grids, resulting in a 64x64x64 representation. The entire dataset had a shape of [1,000, 32, 32, 32]. The 3DGAN was trained using a batch size of 64 and for 500 epochs. Once the generator successfully trained on the encoded datasets, the PyTorch tensor was converted to a NumPy array. To produce a clearer distinction between solid and empty spaces in the generated 3D chairs, a threshold of 0.5 was applied, converting the continuous-valued output to a binary voxel representation (1 for solid and 0 for empty).

### Visualization and Design Exploration

We imported each voxel's center as a point coordinate information into Rhino Grasshopper. By manipulating the sphere's radius parameter, we were able to explore various chair forms derived from the generated points. (Figure 4)

By employing 3DGANs in the design process, we successfully expanded design possibilities beyond the inherent constraints of parameter interpolation. A latent space can be generated that is not confined to the parameter relationships found in traditional parametric models. It also allows for a more comprehensive exploration of design possibilities and facilitates the generation of novel design solutions that would otherwise be unattainable within the boundaries of parametric models alone.

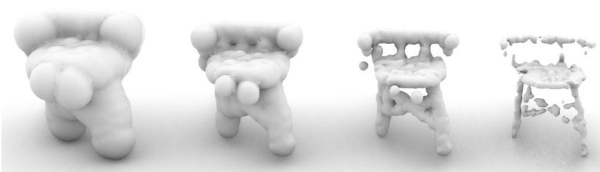

Figure 4: Re-parameterized 3D chair Generation

## Conversational AI/ML in Parametric Modeling

We also explored the integration of ChatGPT, using Rhino Grasshopper (GhPython) code suggested by ChatGPT. This implementation aimed to facilitate an interactive design process where designers could engage in a dialogue with the AI model, allowing them to discover unconventional design processes, thereby creative solutions not confined to predefined parameters.

### Conversation in the ChatGPT Website Platform

The first method uses the online ChatGPT platform as a conversational design assistant. Designers interact with ChatGPT by asking questions, discussing design ideas, and receiving generated GhPython code to create 3D shapes in Rhino Grasshopper. By doing so, the designers could continuously refine their ideas and solicit suggestions from the AI model. With those objectives in mind, the authors formulated the initial prompt as follows:

*”Write a GHpython code that works in Grasshopper. Create a box-shaped geometry to define the outer boundary of the chair, then slice the box horizontally to create multiple layers. On each sliced surface, place a random number of points, then connect these points vertically & horizontally using polylines, with a maximum of 10 lines connected to each point.”*

By interacting with ChatGPT multiple times, the designer can continually refine the design idea and receive AI-generated suggestions to achieve the desired outcome. (Figure 5)

### Integrating ChatGPT API into Grasshopper

We decided to create a bench using the ChatGPT API. Although chairs and benches share similar design attributes, they differ significantly in form and function, requiring a creative approach to formal transformation. The conventional parametric design methodology, which primarily involves the combination of various parameters and variables, might constrain the scope of ChatGPT API, limiting its potential to transcend traditional design methods and templates. Thus, to fully utilize the capabilities of the ChatGPT API and simplify the design process, we developed a new modeling procedure that generates multiple cross-sectional curves using polynomial equations.

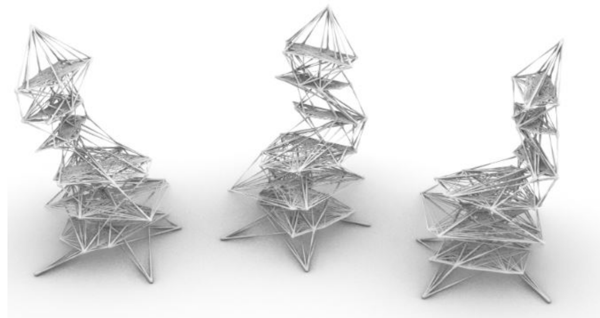

Figure 5: Chair design by Ghpython code from ChatGPT

Firstly, we provided the following instructions to the ChatGPT API:

*”Create two polynomials with three variables: x,y, and z. Seperate the equations with the symbol '&'. You can use sin or cos function”*

Then, ChatGPT API generated the following such polynomials:

”$x^3 + 2x^2y + 3xyz\&cos(x)y^2z + y^3z^2 - 3x^2z^2$”

The authors subsequently utilized these polynomials to define points within the 3D space. These points were then connected to create smooth, curved lines. The authors then utilized these polynomials to define points within a three-dimensional space. These points were interconnected to form smooth, curved lines. The ChatGPT API repeatedly generated multiple curves every 5 seconds based on components and commands given to the grasshopper (See figure XX). The authors subsequently applied 'Loft' to create 3D geometry, which refers to creating a 3D surface or solid by interpolating between multiple 2D cross-sectional curves in Rhino. (Figure 6).

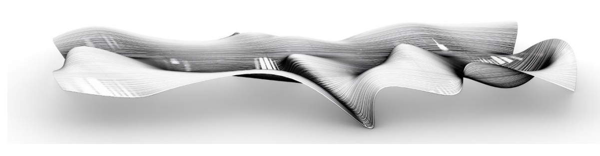

Figure 6: Bench design created by ChatGPT API

The integration created a unique 3D model that displays several features requiring further exploration and analysis. Especially the model presented a sculptural form that deviates significantly from the conventional understanding of a bench. Its design reminds the Verner Panton chair (Kim 2005), challenging conventional delineations of design elements such as the backrest, bench legs, and seat.

## Conclusions

This study has successfully demonstrated the potential of integrating AI/ML techniques with parametric design methodologies to generate innovative and dynamic design solutions. Furthermore, this implementation process shows the possibilities to overcome the limitations of conventional parametric design approaches.

The integration of ChatGPT into the design pipeline remains a significant challenge. While ChatGPT has proven effective in devising new design methodologies, its integration with the design process could be further optimized. Currently, it functions as an independent component, but deeper integration could allow for more real-time, collaborative interaction between the designer and the AI.

We are currently developing the evaluation criteria for AI-generated designs for future work. We need to balance domain-specific aesthetics with broader, potentially domain-independent criteria for creativity. This will require careful thought and potentially novel methods for evaluating and determining the creativity and value of AI-generated artifacts. Moreover, user studies involving designers could provide valuable insights into the practicality and usability of the proposed techniques.

In conclusion, while this study has charted a new direction for AI in design, it represents only the beginning of an exciting journey. The challenges and limitations underscore the scope for future work in this domain. We hope this endeavor stimulates further research and development in integrating AI and design, transforming how we conceptualize, create, and evaluate design artifacts.

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